



Paper to be presented at the
DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

Reaching for the stars: The Contingent Performance Effects of Basic Research Collaboration

Relinde Maria Colen

KU Leuven

MSI

linde.colen@kuleuven.be

Rene Belderbos

KU Leuven

Managerial Economics, Strategy and Innovation

rene.belderbos@kuleuven.be

Bart Leten

KU Leuven

MSI

bart.leten@kuleuven.be

Stijn Kelchtermans

KU Leuven (HUB)

Onderzoeksgroep globalisering, innovatie en competitie

stijn.kelchtermans@kuleuven.be

Abstract

This paper explores the role of university scientists as firms' key partners in basic research. More specifically, it analyses under which conditions joint basic research with university 'star' scientists improves firms' technological performance. Quantile regression analysis for 153 of the most R&D intensive firms in the biopharmaceutical sector in 1995-2003 shows that the benefits of collaboration with university star scientists are highly skewed and concentrated among the top performing firms. These firms' innovative performance is particularly enhanced if the firm and the star scientist also collaborate on applied research. The benefits of this 'translational' collaboration are reinforced when the firm has secured (temporary) exclusive access to the university star scientist. In contrast, when the firm and star do not perform applied research jointly, exclusive access has a negative effect on the firm's innovative performance. We

discuss the managerial implications of our findings for firms seeking to build productive basic research partnerships with university star scientists.

Reaching for the stars
The Contingent Performance Effects of Basic Research Collaboration
between Firms and University Star Scientists

Abstract

This paper explores the role of university scientists as firms' key partners in basic research. More specifically, it analyses under which conditions joint basic research with university 'star' scientists improves firms' technological performance. Quantile regression analysis for 153 of the most R&D intensive firms in the biopharmaceutical sector in 1995-2003 shows that the benefits of collaboration with university star scientists are highly skewed and concentrated among the top performing firms. These firms' innovative performance is particularly enhanced if the firm and the star scientist also collaborate on applied research. The benefits of this 'translational' collaboration are reinforced when the firm has secured (temporary) exclusive access to the university star scientist. In contrast, when the firm and star do not perform applied research jointly, exclusive access has a negative effect on the firm's innovative performance. We discuss the managerial implications of our findings for firms seeking to build productive basic research partnerships with university star scientists.

Keywords: basic research, innovation, star scientists, pharmaceutical industry

1. Introduction

A large body of evidence supports the importance of basic scientific research for advancing economic growth and welfare (Mansfield, 1980; Griliches, 1986; Jaffe, 1989; Adams, 1990; Salter and Martin, 2001; Toole, 2012). Basic research can be defined as activities that are directed towards the general advancement of men's knowledge about the physical world, but without specific commercial objectives (Nelson, 1959). Most basic research is sponsored by governments, and conducted at knowledge institutes, most notably universities. Basic research activities expand the knowledge base available for firms on which they can draw in their applied technological activities (Klevorick et al, 1995). Numerous important technical inventions were the direct result of advances in scientific knowledge resulting from basic research at universities. Mansfield (1995) found that around 11% of firms' new products and around 9% of new processes could not have been developed (or with a substantial delay) in the absence of basic research conducted by universities. Even higher numbers were obtained for the period 1986-1994 (respectively 15% and 11%), suggesting that basic research has increased in importance for industrial R&D over time (Mansfield, 1998).

In general, knowledge interactions between universities and firms have been growing in scale and scope over time (Perkmann and Walsh, 2007; Du et al., 2014), arguably to benefit from each other's expertise and network. Especially the "star" university scientists, defined as highly productive individuals who are leading researchers in their fields, receive special interest from firms (Zucker and Darby, 1996). By means of collaboration, firms get in close contact with university star scientists, giving them direct access to unique (tacit) knowledge (Rothaermel and Hess, 2007), codified scientific knowledge that is not yet published, such as work in progress (Fabrizio, 2009), and a large social network within the scientific community (Murray, 2004; Subramaniam, 2013).

While most basic research is concentrated at universities, there are also good reasons for firms to conduct in-house basic research. By performing basic research, firms can increase their understanding of the technological landscape in which they search for inventions (Rosenberg, 1990; Fleming and Sorenson, 2004), hire researchers that are reluctant to work for firms in which they are not allowed to do basic research and publish scientific findings (Henderson and Cockburn, 1994; Hicks, 1999), improve their absorptive capacity for external research

(Gambardella, 1992; Leten et al., 2011) and get an access ticket to R&D partnerships with universities (Liebeskind et al., 1996).

Prior studies have confirmed that the benefits of in-house basic research are greater when basic research is conducted in collaboration with university scientists (Henderson and Cockburn, 1998; Fabrizio, 2009) and several studies have documented positive performance effects of firm-university collaboration in general (Furman and MacGarvie, 2009; Belderbos et al., 2004 and 2014; Du et al. 2014). In addition, studies have established that the positive impact of research universities on nearby firms is due to specific collaborations with star scientists rather than generalized knowledge spillovers of the university (Zucker et al., 1998). It has been shown that the number of research collaborations between firms and university star scientists has a positive effect on the number and average quality of firm innovations (Zucker and Darby, 2001; Zucker et al., 2002). While these studies have suggested that collaborating with academic star scientists is likely to result in an improved innovation performance for the firm, little is known about the contingencies for these effects to occur. Since basic research entails large investments while outcomes are uncertain, it is crucial to understand which modalities of these partnerships are prone to increase the benefits of star-firm collaborations.

This paper contributes to our understanding of how excellence in science strengthens firms' innovativeness. We investigate two structural characteristics of basic research collaborations with star scientists. First, we examine whether star scientists assist the firm in (follow-up) applied research, taking up a 'translational' role between basic research and technological applications. To succeed in the hard translational step from basic research results to commercial development, it is crucial to understand the two worlds and recognize opportunities to link science and technology. Second, we examine whether the firm may benefit from (temporary) exclusivity in the collaboration with star scientist as this mitigates the spillovers of what is arguably unique and highly specialized knowledge to rival firms who may free ride on these research efforts. In sum, we expect that the translational character of the scientist and the exclusiveness of the relationship will act as important moderators for the effectiveness of the star-firm collaboration in basic research, as measured by the innovative performance of the firm.

To test our hypotheses, we make use of a panel dataset on the patent and publication activities of 153 leading innovating pharmaceutical and biotechnology firms. The sample firms have

headquarters in the United States, EU and Japan and their technological performance is observed over a period of nine years (1995-2003). Information on scientific publications in the Web of Science database is used to examine firms' basic research activities and collaborations with university star scientists. Star scientists are identified as individuals leading their field(s) in terms of the number of scientific publications and citations. We use quantile regression analysis to explain firms' yearly innovative performance, measured by citation-weighted patent counts, as a function of basic research collaboration with university stars, accounting for the aforementioned modalities of these partnerships and controlling for a range of productivity determinants.

We find that basic research collaboration with stars increases inequality in technological performance across firms since the effect of such partnerships only affects the upper quantiles of the innovation performance distribution. Collaborating with 'translational' stars – who also engage in joint applied work with the firm – entails an additional performance premium, again at the upper end of the distribution. The firm accumulates further benefits if it manages to temporally secure exclusive access to the translational star. Interestingly, we find that higher rates of exclusivity to non-translational stars – who only do basic research with the firm – suppress the citation-weighted patent output of the most productive firms.

The remainder of this paper starts by grounding our analysis in two related streams of innovation research, i.e. innovation studies on the role of basic research, and the economics of science literature dealing with star scientists. In section three we discuss the rationale behind our hypotheses. Section four introduces the data and explains our empirical methodology. The empirical results are discussed in section five and in the final section we recap the main findings and their implications, summarize work in progress and suggest avenues for further research.

2. Literature and Background

Basic Research and Firm Performance

Innovation studies have delivered abundant evidence of the important role of basic research in driving innovation and economic growth (Mansfield, 1980; Griliches, 1986; Jaffe, 1989; Adams, 1990; Salter and Martin, 2001; Toole, 2012). To what extent it is rational for firms to

be involved in basic research has however been subject to a long debate among economists. Nelson (1959) argues that firms are reluctant to invest in basic research due to high degrees of uncertainty, long time frames to bear fruit, and appropriability problems. More recent contributions (Rosenberg, 1990; Gambardella, 1992; Fleming and Sorenson, 2004; Cassiman et al., 2008), on the other hand, argue that there are good reasons for private firms to invest in-house in basic scientific research.

A first reason for firms to engage in basic scientific research is to develop a deeper understanding of the technological landscape in which they search for inventions (Gambardella 1992). Basic scientific knowledge allows firms to anticipate the results of research experiments without performing them, helping to prioritize research avenues and to avoid costly research trials that lead to low-value outcomes (Rosenberg, 1990; Fabrizio 2009). In other words, basic scientific knowledge informs firms on the success probabilities of different directions to conduct applied research (Fleming and Sorenson, 2004; Cassiman et al. 2008). Second, it also helps to evaluate the outcomes of applied research and to get a more accurate and encompassing perception of its implications (Rosenberg, 1990). Further in-house basic research helps to recruit scientists that prefer to work in firms that conduct in basic research and where they can publish their research findings (Henderson and Cockburn, 1998; Hicks, 1999). Finally, in-house basic research generates absorptive capacity: it leads to knowledge and skills required to understand and utilize the findings of basic research conducted elsewhere, most notably at universities (Gambardella 1992, Leten et al. 2011).

Prior empirical studies (e.g. Gambardella, 1992; Cockburn and Henderson, 1998; Fabrizio, 2009; Leten et al., 2011, with the exception of Lim, 2004) have found positive performance effects of conducting in-house basic research. Using samples of US pharmaceutical firms, Gambardella (1992) and Cockburn and Henderson (1998) found that firms which perform more basic research, measured by the number of firm publications, produce a greater number of patented inventions. Similar findings were obtained by Leten et al. (2011), using a global sample of pharmaceutical firms and a more accurate indicator of basic research, i.e. the number of publications in basic research journals. In contrast to these studies, Lim (2004) found no effect of in-house basic research on the patent performance of pharmaceutical firms, and even a negative effect for semiconductor firms. Della Malva et al. (2013) examined whether the own pursuit of basic research puts firms in a better position to generate breakthrough inventions which have a large impact on subsequent inventive activities. They found that the involvement in basic research helps firms to generate breakthrough inventions.

Surprisingly, the benefits of basic research are not found in the technology fields that are directly associated with the basic research, but in other areas of the firms' technology portfolio. This result is consistent with a view of basic research as a "map" that guides firms into new research directions (Rosenberg, 1990; Fleming and Sorenson, 2004).

Further, studies have found that the benefits of performing in-house basic research are greater when basic research is conducted in collaboration with universities (Cockburn and Henderson 1998, Fabrizio 2009, Leten et al. 2010, Zucker et al. 2002). While it is a Sisyphean task for a firm's R&D-department to remain up-to-date with all the relevant scientific advances, university partners are recommended to provide guidance to and expertise in relevant research areas (Cassiman and Veugelers 2006). The firms receive access to relevant preliminary research (Fabrizio 2009) and obtain (tacit) knowledge of university scientists, which cannot be derived solely from journal articles (Arora and Gambardella 1990, Cockburn and Henderson 1998). Consequently the partnerships allow firms to build faster on recent basic research findings in their own applied research activities (Fabrizio, 2009).

University Star Scientists

Within the economics of science literature, studies have demonstrated a highly skewed distribution of research output across scientists. This is a robust research finding dating back to Lotka (1926), who found that the number of scientists producing n papers is inversely proportional to n^2 , and can be largely explained by a host of individual and institutional factors (e.g. Kelchtermans and Veugelers, 2011). The small number of scientists that are responsible for a disproportionately large share of the research output can be labeled as star scientists. As an indication of the "stardom" of star scientists, Zucker et al. (1998) found that while the 327 stars they identified comprised only 0.75% of the total scientific authors in Genbank (the NIH genetic sequence database), they accounted together for 17.3% of the published articles, nearly 22 times as many articles per star as the average non-star scientist.

Star scientists are not only more productive than non-star scientists, they also have large networks of collaborators. Hess and Rothaermel (2012) studied the collaboration networks of star scientists in pharma and biotechnology, and found that stars have many connections to non-stars and serve as scientific hubs in collaboration networks. Although star scientists made

up only a small portion of the scientist population (<1%), in biotech (pharma) 13% (27%) of non-star scientists have coauthored with star scientists (Hess and Rothaermel, 2012).

Most of the star scientists are affiliated at knowledge institutes and universities. Zucker et al. (1998) found that 97.6 per cent of the stars within Genbank were affiliated to a university or research institution. Multiple scholars have indicated that scientists are reluctant to commit themselves full-time to a firm, as it may impede publishing and actively contributing to the scientific field (Murray, 2004; Stern, 2004). From the perspective of an innovating firm, the scarcity of high-quality and well-connected scientists implies that it is of strategic importance to access the best human capital through research collaborations (Hess and Rothaermel 2011, Zucker et al. 2002). A small number of studies have shown that the number of research collaborations between firms and university star scientists has a positive effect on the number and average quality of firm innovations (Zucker and Darby, 2001; Zucker et al., 2002). These studies did not distinguish between collaborations in basic and applied research, and did not study the modalities under which (basic research) collaborations with university star scientists are most effective.

3. Hypotheses

Basic Research Collaborations with Star Scientists (baseline hypothesis)

Firms are expected to benefit from basic research collaborations with university star scientists in several ways. First, partnerships with star scientists grant firms access to scientists with extraordinary research capabilities who are leading their fields in terms of quantity and quality of research outputs (Zucker et al., 1998, 2002). Access to extraordinary scientists is important in basic research since basic research is a complex activity, that is characterized by high levels of (technical) uncertainty. Collaborations with star scientists often lead to extensive debate, exchange of ideas and discussions. This provides firms with access to tacit knowledge of the star scientists (Cockburn and Henderson, 1998) and codified scientific research of stars that is not yet published (e.g. work in progress), allowing firms to build faster on recent basic research findings in their own applied research (Fabrizio, 2009).

Second, collaborations with star scientists provide firms access to the large scientific networks of the star scientists (Hess and Rothaermel, 2012), and so provide useful contacts, recognition and wider knowledge spillovers (Murray, 2004; Luo et al., 2009). Finally, the university star scientist may strengthen the firm's absorptive capacity for basic research by helping it to recognize and understand advances in basic scientific research (Cockburn and Henderson, 1998) and further enhance the research capabilities of the firm's R&D department improving the overall quantity and quality of research conducted in the firm. This results in the following baseline hypothesis on the involvement in basic research with star scientists.

H₀: Collaboration with university star scientists in basic research improves the innovative performance of firms.

Translational Research with Star Scientists

Building on prior research into the obstacles of effective university-industry collaborations (e.g. Bruneel et al., 2010), we argue that bridging between the deep scientific capabilities of star scientists and the more applied research of firms is not trivial and is conditional on the mode of collaboration with the star scientists. The fact that academic star scientists are strongly driven by their taste for science and the priority-based scientific reward system (Merton, 1957; Dasgupta and David, 1994) contrasts with the way that firms deal with science i.e. driven primarily by the aim to exploit it from a profit-maximizing perspective (Rosenberg, 1990; Arora and Gambardella, 1994). These different objectives, and the resulting distinctive capabilities, have been considered in the literature as the basis for a division of labor in the innovation process, where one party specializes in 'invention' while the other focuses on 'innovation' (Arora and Gambardella, 1994). However, as Arora and Gambardella (1994) argue, division of labor in innovation poses greater challenges than in (for example) manufacturing since knowledge is difficult to transfer in arm-length relationships. That the basic-applied translational step in innovation is hard, is illustrated by the 'fall-out-rate' on the road from scientific breakthroughs to industrial application: it takes on average 17 years for only 14% of new scientific discoveries to enter day-to-day clinical practice (Westfall et al., 2007). Our analysis ties into this issue and contributes to understanding to what extent specialization in basic research collaborations between firms and academic stars – or deliberately avoiding such a clear-cut role division - pays off for the firm.

The idea that scientists may engage in applied research jointly with firms departs from the stereotypical view that scientists are only interested in (basic) research and publishing. Recent studies in the economics of science literature have indicated that there are (basic) scientists who have a preference to also do applied work (Stokes, 1997; Sauermann and Roach, 2012; Sauermann and Stephan, 2013). Moreover, multiple researchers have indicated that there is a two-way interaction between basic and applied research (Rosenberg, 1990, Sauermann and Roach, 2011). Just like basic results can lead to follow-up applied research, scientists can detect new and promising directions for basic research when performing applied work. Meyer (2006) found that the publication output and quality of scientists that both publish and patent is higher than those that specialize in one activity. In short, it is certainly possible that scientists are willing to complement joint basic research with firms with applied research as it may fall within their interest and it may even improve their performance in basic scientific research.

In this respect, we expect that the university star scientist can play a pivotal role for the firm's innovative performance by being involved in applied research and this for two reasons. First, a scientist that is active in both basic and applied research will be able to bridge the two distinct worlds (Gittelman and Kogut, 2003; Rothaermel and Hess, 2007; Baba et al. 2009; Subramanian et al., 2013). Gittelman and Kogut (2003) stress that the selection criteria for an important scientific invention follow a different logic than the criteria for a valuable innovation in the commercial world. A 'bridging' or translational scientist is capable to assess both sets of criteria and to discover new opportunities to connect science and technology. Second, scientists possess knowledge that is valuable within the development process and that cannot be retrieved from descriptions in scientific publications that report on their basic research (Agrawal, 2006; Sorenson, 2006; Fuller and Rothaermel, 2012). Scientists contribute insights, experience, behavioral practices and memory of trial and error. Even if basic research was conducted jointly, the full value of scientific knowledge may not come to surface without the involvement of the scientist in development activities (Sorenson, 2006). It follows that collaborative basic research with a 'translational star' - a star university scientist who is next to basic research also involved in applied work with the firm - generates an innovative performance premium for the firm.

H₁: The innovation premium of a star-firm collaboration in basic research increases if the university star scientist is also involved in applied research with the firm.

Exclusive Access to Star Scientists

The star scientist can be seen as a crucial resource within the innovation process, giving direct access to unique scientific knowledge (Rothaermel and Hess, 2007). However scientific knowledge is believed to be partly a public good and therefore freely available to other firms (Arrow, 1962; Nelson, 1959). Consequently, the collaborating firm will seek to prevent the knowledge from spilling over to competitors who can then free ride on its investment (Sorenson, 2006). In particular, rival firms who are engaged in parallel research projects with the same university scientist may get access to the scientist's expertise, even if there are contractual limitations that prohibit the sharing of certain pieces of knowledge.

Fortunately, knowledge is not a pure public good, available to everyone. As scholars have indicated, scientific knowledge is not a ready-made input (Gittelman and Kogut, 2003). Learning and understanding scientific results requires time and absorptive capacity, i.e. in-house experience in basic research (Cohen and Levinthal, 1989; Kittelman and Kogut, 2003). Further, the knowledge necessary to develop a new technology may (still) be embedded in the inventor as it is tacit or not yet been codified (Zucker et al., 1998). In short, firms will experience difficulties when entering a new technology and these difficulties will drop in time and with proximity to scientific discoverers (Zucker et al., 2002). Consequently, when a star scientist exclusively collaborates with the focal firm, the firm will be able to temporarily safeguard unique access to scientific knowledge and obtain a first mover advantage in knowledge. Even if the basic research findings are published, the lack of required tacit knowledge will make it difficult for competitors to put the basic results to productive use (Cohen and Levinthal, 1989), and the firm can still obtain a crucial first-mover advantage in the development phase (in particular if this culminates in a patent application).

Besides the strategic protection against competitors, an exclusive connection with the star scientist can also directly affect the quality of the joint research. One direct effect is the greater availability of the star scientist, which can result in more intense and frequent interactions. Second, the firm and the scientist will obtain a more open collaborative relationship if it is free from outsiders. The firm will be more willing to share valuable trade secrets and the star scientist may be less restricted in her communication due to secrecy agreements stemming from other projects. The resulting higher levels of trust will lead to a

more fluent interaction, and the freedom to talk will lead to a larger scope of subjects and directions of research to be discussed. In turn, the increased quality of the interaction will reinforce the success rate of the collaboration (Bruneel et al., 2010; Tartari et al., 2012; Forti et al., 2013; Plewa et al., 2013). From the above considerations, it follows that the performance effect of star-firm collaborations in basic research are more pronounced if the firm has secured (temporary) exclusive access in research to the academic star scientist.

H₂: The innovation premium of a star-firm collaboration in basic research increases if the firm has secured exclusive (temporary) access to the star scientist.

4. Data and Empirical Model

Sample firms

To answer the proposed research questions, we constructed an extensive panel dataset on the patent and publication activities of 153 pharmaceutical and biotechnology firms in 1995-2003. The firms have headquarters in the United States, the EU or Japan and are the largest R&D spenders (in absolute terms) in the pharmaceutical industry.¹ In line with our research focus we restrict this initial sample to those 64 firms that have at least one co-publication with an academic star in basic science during 1991-2001. The sample is slightly unbalanced due to merger activity after the first year of observation. For example, AstraZeneca was formed in 1999 by a merger of the firms Astra and Zeneca, and is included in the panel dataset from 2000 onwards.

Patent data

The firms' innovative performance is based on patent data. Patent indicators lend themselves to empirical analysis for multiple reasons (Pavitt, 1985; Basberg, 1987; Griliches, 1990). First, patents contain detailed information on the technological content, owners and prior art of patented inventions. Further, patent data are objective in the sense that they have been processed and validated by patent examiners, and finally, they cover long time series. Like any indicator, patent indicators are also subject to a number of drawbacks, the principal ones

¹ As reported in the 2004 EU Industrial R&D Investment Scoreboard. This ranking lists the top 500 corporate investors in R&D whose parent is located in the EU, and the top 500 companies whose parent is located outside the EU (mainly US and Japan), based on corporate R&D expenditures in 2003.

being that not all inventions are patented and those that are patented vary in their technical and economic value (Trajtenberg, 1990; Lanjouw et al, 1998; Gambardella, 2008). The first problem can be addressed by limiting patent analyses to industries with high patent propensities and studying firm-level patent time series. The ‘value problem’ can be taken care of by weighting patent counts by the number of forward patent citations (Trajtenberg, 1990; Harhoff et al, 1999).² Both approaches are followed in this paper.

Another methodological issue related to using patent data in a firm-level analysis is that company names in patent databases are not unified and patents may be applied for under names of subsidiaries or divisions of a parent firm. Therefore, patent data have been collected at the consolidated parent firm level, by searching for patents under the name of the parent firm as well as all their majority-owned subsidiaries. For this purpose, yearly lists of companies’ subsidiaries included in corporate annual reports, yearly 10-K reports filed with the SEC in the US, and, for Japanese firms, information on foreign subsidiaries published by Toyo Keizai in the yearly ‘Directories of Japanese Overseas Investments’, were used. The consolidation was conducted on a yearly basis to take into account changes in the group structure of sample firms due to acquisitions, mergers, green-field investments and spin-offs. Acquisitions, and their patent stocks, are considered part of a parent firm from the year the acquisition transaction has been completed. The innovative performance of the sample firms, our dependent variable, is measured as the number of patent applications at the European Patent Office (EPO) of a parent firm in a year, weighted by the number of forward patent citations received by those patents over a fixed time window of 4 years. The number of forward patent citations is calculated on a fixed 4-year time window because the number of forward citations to any patent depends on the length of the citation window (Hall et al, 2005; Trajtenberg, 1990). Forward patent citations are calculated on the EPO patent citation database of Webb et al. (2005) and are calculated for all citing EPO patents and national patents with EPO patent equivalents.

² In particular in the pharmaceutical industry, patents and patent citations are a relevant indicator of innovative performance and closely linked to market valuation (Hall et al., 2005). Magazzini et al. (2012) show that patents protecting chemical compounds that successfully get through clinical trials get significantly more citations than patents pertaining to compounds that fail in initial trials (but often get a second life in another application), while patented compounds that do not make it to such trials receive no or much smaller numbers of citations.

Publication data

Scientific publications in peer reviewed international journals are used to examine basic research activities of firms. Prior work has argued that publication counts represent investment levels in (basic) science and proxy for the extent to which companies are involved in the scientific community (Gambardella, 1992, 1995). In addition, publication rates are a timely measure of firms' involvement in basic research since the turn-around time of publications in most exact sciences fields is short (Kaplan et al, 2003). Publication data are extracted from the Web of Science database. Publication data will, like the patent data, be collected at the consolidated firm level. This approach consists of identifying all publications on which the parent firms, or their subsidiaries, are listed as publishing institutes. Firms' involvement in *basic* research will be measured by the (consolidated) number of firm publications in basic research journals, using the CHI journal classification scheme which classifies journals in different levels, from applied to basic research (Hamilton, 2003; Thursby and Thursby, 2011; Leten et al., 2011).

In prior work and consistent with other research (Cockburn and Henderson, 1998; Fabrizio, 2009), we have developed string-matching algorithms to identify firm publications that are jointly published with universities, our indicator of university-firm collaborations in basic research. While industry-university interactions may also occur through other channels³, prior research has validated the usage of co-publications as reliable indicators of collaborative research (Cockburn and Henderson, 1998; Fabrizio, 2009; Leten et al, 2011). In particular, co-publications are considered a reliable indicator of research collaborations as the co-authors are typically involved in the formulation of the research problem as well as the actual research activities (Laudel 2002). Melin and Persson (1996) suggest that only five percent of surveyed scientists reported instances of collaboration not resulting in co-authored papers. Studying co-publications of a set of European and Japanese firms in the electronics and pharmaceuticals sectors (the latter being our sector of investigation), Hicks (1996) concluded that the large majority (84-93%) of the co-publications of these firms involved at least some sort of collaboration. In sum, most collaborations result in co-authored publications, and most co-publications do reflect actual research collaborations.

³ Other means of exchanging knowledge include citations of university publications in firm publications or patents, contract research, etc. See Schartinger et al. (2002) for a comprehensive study.

Star scientists

A known issue of the Web of Science publication records is that prior to 2008 they do not contain a one-to-one link between authors and affiliations. Exploiting the variation of co-author teams across publications combined with the occurrence of ‘firm-only’ publications, we disentangle academic and corporate scientists, with the former representing 54% of the total set of 412,465 authors.

To determine the university star scientists, we considered the 4,568 academics who had at least 10 co-publications with firms.⁴ We constructed their full publication and citation records⁵ from 1991 to 2009 in five scientific disciplines (using the Web of Science subject categories) relevant for the broader field of the life sciences, namely biosciences, biomedical research, general and internal medicine, non-internal medicine specialties, and neuroscience & behavior. In line with Hess and Rothaermel (2007, 2012), we define star scientists as researchers that have a publication or citation count (the latter using a 3-year forward citation window) that exceeds the average performance in the discipline by at least 3 standard deviations. We make this comparison within each of the 5 considered scientific disciplines to control for discipline-specific publication and citation patterns (e.g. Kelchtermans and Veugelers, 2013). The productivity levels achieved by stars corroborate the rationale that highly able scientists tend to opt for an environment where they can maximize the prestige rewards associated with their ability (typically academia). Hence, the highly selective group of star scientists is arguably quite homogenous in terms of ability, which is an essential control factor when analyzing the effects of science on firm productivity (e.g. Stern, 2004). This identification procedure results in 472 university star scientists⁶ who on average publish 25 papers per year, of which 4% are jointly published with the sample firms. In total, we count 1,397 star-firm collaborations, i.e. co-publications, in basic research. While all academic stars have basic science publications with the sample firms, the majority of stars (57.4%) also publish applied work with firms.

⁴ This restriction is merely intended to reduce the magnitude of the data processing task. We verified that this cut-off has no impact on the identification of researchers as stars.

⁵ To reduce the problem of homonyms in the identification of star scientists, each of the 4,568 academic scientists was matched with her most frequent affiliation with the help of the Centre for R&D Monitoring (ECOOM) at the University of Leuven. Using the combined name-affiliation information, we retrieved the complete publication information of these academic scientists.

⁶ This includes 155 ‘publication stars’, 150 ‘citation stars’ and 167 scientists who exceed the star threshold (in at least one of the five disciplines) for both publications and citations.

The translational characteristic of a star scientist is defined at the firm-star level. More specifically, a star is characterized as ‘translational’ vis-à-vis a given firm if (s)he appears at least once as a co-author on an applied research publication of the focal firm during the analysis period(1995-2003). Exclusivity of a firm-star collaboration is defined as the absence of co-publications of the star with other firms⁷ during the two years prior to the focal publication. In the empirical analysis, to avoid collinearity between the collaboration variables, each form of collaboration is defined in a relative way, rather than as an absolute count of publications. More specifically, the ‘hierarchy’ of collaborations is composed of the following categories: basic research collaboration with academia → with academic stars → with (non-)translational stars → in exclusivity with (non-)translational stars. In terms of variable definition this means that, for example, collaboration with *translational* stars is measured as the number of basic research publications with translational stars divided by the number of basic research publications with (both translational and non-translational) stars. Analogously, *exclusive* collaborations with translational stars are measured as the percentage of basic research publications with translational stars for which the firm was the only one co-authoring with the star in the two years preceding the publication.

Descriptive Statistics & Empirical Methodology

A key feature of the data is that the technological performance distribution is very skew, with a few firms applying for a high number of (citation-weighted) patents every year, while the bulk of firms show a (relatively) more modest output.⁸ To further illustrate this, Figure 1 relates the distribution of technological performance, measured by the citation-weighted patent output of firms in year t , to firms’ involvement in basic research in years $(t-4, t-1)$. A few firm-year observations have been highlighted to illustrate heterogeneity among firms. For example, Biogen Idec innovates at a lower rate than the much larger Merck & Co. Note that we will control for firm size in the regression analysis. Further, there is considerable intra-firm variation in both performance and basic science intensity, the latter measured as number of publications in basic science journals divided by million US dollars of R&D expenditures (shown on the left vertical axis). For example, there is a clear downward trend in the basic

⁷ The exclusivity is defined not by considering only the 64 sample firms who jointly perform basic research with stars, but by checking collaboration of the star with the broader group of the 153 firms in the pharmaceutical industry (cfr. supra).

⁸ The average number of yearly citation-weighted patents across firms is 159, but with a very large standard deviation of 222.

science intensity of Merck & Co. Finally, the vertical axis on the right of the graph shows firms' share of basic research with academic scientists and with academic stars. While both remain fairly stable across the performance distribution, it is noteworthy that also the smaller and/or less productive firms engage to the same extent (in relative terms) in collaboration with stars, if not more. This is a first indication that innovative performance does not solely depend on the fact *whether* a firm collaborates with a star and that 'how' one collaborates may be of significant importance.

The highly skewed performance distribution calls for an appropriate empirical approach. In particular, the clear departure from normality suggests that the most salient insights in the data may remain below the radar if one only considers the effects of covariates on the conditional mean of performance. Therefore, we employ quantile regression analysis, which allows estimating the effects of the collaboration variables on different quantiles of the performance distribution. Since the dependent variable (citation-weighted patents) is discrete, we use Machado and Santos Silva's (2005) technique of imposing artificial smoothness ('jittering') to allow for consistent estimation of the quantile parameters. Accordingly, Table 1 further exposes the variation across the performance distribution by reporting the 'localized' means of the covariates i.e. including those observations that fall within a given percentile range of innovative performance. The table also introduces the control variables that will be included in the regression analysis: R&D expenditures (log in t-1), patent intensity (patents from t-1 to t-4/R&D in t-1), technological diversity (inversed Herfindahl index of the number of patent classes), reliance on basic research (average number of basic NPR's on patents), involvement in basic research (number of basic research publications/R&D), the share of joint basic-research with university and dummies for biotechnology and instrumental companies. Instrumental firms are also located in a market that is less basic research intensive than pharmaceutical or biotechnology. Within the correlation matrix shown in table 2, this is clearly indicated by the negative correlations between the instrument dummy and all the innovation activities. Also, biotech firms operate within a different market than pharmaceutical firms. They do not have stable revenues from mass-production drugs resulting in lower R&D expenses, higher reliance on innovation and more risk taking. Additionally, we will control for the extent of R&D expenses and the number of technology fields in which the firm is active, as firms with a large and diversified set of R&D projects may have more opportunities to benefit from the star's knowledge. Further, we incorporate the amount of in-house research of the firm by accounting for its publications in basic journals. As we are

interested in the specific effect of joint basic research with university star scientists, it is necessary to further control for the more general links to universities, like gathering knowledge from academic papers and collaborations with a non-star scientist.

5. Empirical Results

Table 4 shows the results of a model that estimates the effects of the covariates on 6 different quantiles of the dependent variable, that is, firms' yearly citation-weighted patent output. We include the three quartiles (25%, 50%, 75%) and a more fine-grained set of quantiles to study the upper part of the distribution (90%, 95%, 99%), the intuition being that collaboration with stars may primarily affect the most productive firms and/or the most valuable innovations.

First, the variables that control for firm size (measured by the log of R&D expenditures) and patent propensity are associated with a higher technological performance throughout the distribution. Further, technologically more diversified firms show a higher performance, though primarily at the lower and upper end of the distribution. An increased reliance on external basic science in the preceding four years (measured by the number of non-patent references to basic science publications for which the firm was not a co-author) decreases performance in the left tail while it further increases performance of the most productive innovators. With respect to the firm's own involvement in basic research, the results show that a higher basic science intensity lifts the performance of the less productive innovators.⁹

Turning to the variables that capture collaboration in basic science, a first finding is that the value of collaborating with academic scientists can be primarily attributed to the star scientists and that it is concentrated at the very top (99%) of the distribution.^{10,11} In other words, collaborating with academic stars for basic research increases inequality in technological performance across firms since it pushes up only the upper tail of the performance

⁹ Robustness checks (not reported here) where we include only the control variables and the basic science intensity (i.e. omitting the collaboration variables) show that basic science intensity has a positive impact on both the lower end of the distribution (25%) and the extreme upper end (99%).

¹⁰ Robustness checks including only the collaboration variables for the share of basic science with academics and the share with academic stars (while keeping in all other variables of the full model) show that the effect of stars is located in the 95-99th percentile while the unconditional share with academic scientists is statistically significant for the 99th percentile.

¹¹ Note that, while the extreme right tail of the distribution is naturally very selective in terms of the firms that operate there, more than 10 sample firms show performance levels above the 90th percentile.

distribution. This finding is consistent with prior literature, which has indicated that firms do not benefit equally from external knowledge due to differences in (largely unobserved) firm characteristics. Examples include the presence of absorptive capacity to evaluate, understand and integrate scientific frontier knowledge, or skills in translating insights from basic research into applied and clinical research, and ultimately new inventions (Cohen and Levinthal, 1989 and 1990; Cassiman and Veugelers, 2006; Fabrizio, 2009; Hagedoorn and Wang, 2012). These differences in firms' endowments have implications for their ability to learn from external research findings. In particular, Teece et al. (1997) have argued that the learning effect depends on the commonality between the internal knowledge base of the firm and the external research findings which it intends to exploit in its technology activities. In our setting of firm-star collaborations, this means that the firm's in-house research capabilities need to be on par with those of the star scientist. This rationale is consistent with the localized effect of firm-star collaboration in the upper end of the distribution.

The coefficients of the remaining collaboration variables provide a test of our two hypotheses. First, the positive and statistically significant coefficient for translational stars, which kicks in at the 90th percentile, confirms that joint basic research with university star scientists is more beneficial if the firm and the star also do joint applied work, relative to doing 'only' basic research with academic stars. In other words, the commitment of the academic star in translational research is, from a firm perspective, an important factor in explaining the success (from a firm perspective) of such partnerships. Second, we find a dual effect of firms' exclusive access to academic stars, with a positive impact on technological performance for exclusive access to translational stars (but only in the 99th percentile) versus a negative effect for exclusive access to non-translational stars (in the 90th to 99th percentile). The former supports our hypotheses that an exclusive relationship may generate a first-mover advantage or improve the quality of interaction. The latter may suggest that firms (on average) 'overinvest' in relationships with stars who are not involved in converting the insights at the scientific frontier into practical applications. An alternative explanation points to negative selection effects: the involved firms may underestimate the difficulty of translation and because of that reason may team up with stars who are unable - or unwilling - to assist the firm with transforming their basic results into actual innovations.

Finally, note that the quantile function is not a linear operator so the parameter estimates cannot be interpreted as marginal effects. A calculation of the marginal effects at the 'localized means' in different quantile ranges (as shown in Table 2) shows that the magnitude

of the effects on the upper tail of the distribution are substantial. For example, the marginal effect on the 90th percentile of technological performance of a 1% increase in the share of basic science in collaboration with translational star scientists amounts to 252 citation-weighted patents, or about 1 standard deviation (222). In other words, while the effect of tapping into the best deep science capabilities is confined to the best innovators and the most valuable innovations, the impact is by no means negligible.

6. Conclusions

Our study has provided a number of important insights into the conditions under which joint basic research with university star scientists improves the technological performance of firms. While the benefits of such collaboration are unevenly distributed and associated with high performing firms, these firms can increase the effectiveness of collaborative research by also jointly performing applied research with the star scientist and by keeping the collaborative relationship exclusive, at least temporarily. More fundamentally, our research underscores that while a firm may improve its innovative performance by collaborating with the ‘best and brightest’ inside academia, there is a clear managerial challenge to make such partnerships reach their full potential. In particular, the positive effect of more comprehensive collaborations (i.e. including joint applied work), further leveraged by the exclusivity of the arrangement, represent handles for firms to build productive partnerships. Widening the scope of collaborations beyond basic research has implications for the search process of the firm, as not every star may have the capabilities for, or be interested in, applied work. Further, concluding a partnership that offers the firm exclusive access, at least in the short run, to the most topical work of the star and its tacit properties has competitive implications. For one thing, the firm needs to be aware of the strategies of its competitors - who may aim to team up with the exact same star - if it is to secure a first-mover advantage. The finding of an apparent negative impact of exclusive access to stars who only engage in joint basic research further suggests the importance for firms of making the right choices in their strategies for accessing superior human capital.

In future research we aim to refine our analysis in several ways. First, we can extend the search for star scientists by relaxing the criterion of 10 co-publications with focal firms. Second, we aim to improve the name disambiguation by linking our sample scientists with the

Author-ity dataset (Smalheiser and Torvik, 2009) which contains 60 million disambiguated author names. Third, we can explore different definitions of translational star scientist, including engagement in applied research in general. Fourth, we will examine broader measures and time frames for exclusivity. Fifth, we aim to include a broader set of controls among which firms' technology alliances. Finally, we will perform robustness checks, most importantly with other dependent variables like the number of products in development.

Beyond this work in progress, we advance the following avenues for further research. First, while we believe the results are likely relevant for other science-intensive industries, our findings need to be corroborated beyond the life sciences. Further, a more fine-grained characterization of stars may allow for more attenuated findings. In particular, while it is challenging to collect such micro data, information on (part-time) corporate affiliations of stars or their transfer to industry would permit further insights with respect to the precise commitment of the star to translational science. A final issue with implications for external validity is the potential endogeneity of star collaboration. In particular, the 'best' firms - in terms of basic science capabilities, innovation track record, etc. - may be more likely to successfully team up with academic star scientists. Hence, our findings primarily apply to firms that see basic research collaboration with stars as a key component of their R&D strategy and may be of lesser importance for firms with strategies not so much geared towards working with leading academic scientists. Note that our empirical approach does mitigate the issue of selection since the effects that we find occur in the upper end of the distribution, which is occupied by the most innovative firms. However, future work providing insights in the matching process between firms and stars would constitute a valuable addition to the results presented here. Finally and also related to the latter issue, we believe further fieldwork is necessary to better understand the antecedents of joint basic research collaborations between firms and stars. In addition, qualitative work will aid in understanding to what extent firms deliberately aim for partnerships that comprise not only basic but also joint applied work, and whether they need to exert significant effort to reach (temporal) exclusivity of those arrangements.

7. References

- Adams, Y. D. (1990). Fundamental stocks of knowledge and productivity growth. *Journal of Political Economy*, 98, 673-702.
- Agrawal, A. (2006). Engaging the inventor: exploring licensing strategies for university inventions and the role of latent knowledge. *Strategic Management Journal*, 27, 63-79.
- Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In *The Rate and Direction of Inventive Activity*. Princeton University Press.
- Baba, Y., Shiijo, N., & Sedita, S. (2009). How do collaborations with universities affect firm's innovative performance? The role of 'Pasteur scientists' in the advanced materials field. *Research Policy*, 38, 756-764.
- Belderbos, R., Carree, M., & Lokshin, B. (2004). Cooperative R&D and firm performance. *Research Policy*, 33, 1477-1492.
- Belderbos, R., Tong, T., & Wu, S. (2014). Multinationality and downside risk: The roles of option portfolio and organization. *Strategic Management Journal*, 35(1), 88-106.
- Bruneel, J., D'Este, P., & Salter, A. (2010). Investigating the factors that diminish the barriers to university-industry collaboration. *Research Policy*, 39, 858-868.
- Cassiman, B., & Veugelers, R. (2006). In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition. *Management Science*, 52(1), 68-82.
- Cassiman, B., Veugelers, R., & Zuniga, M. P. (2008). In search of performance effects of (in)direct industry-science links. *Industrial and Corporate Change*, 17(4), 611-646.
- Cockburn, I., & Henderson, R. (1998). Absorptive capacity, co-authoring behaviour, and the organization of research in drug discovery. *The Journal of Industrial Economics*, 46(2), 157-182.
- Cohen, W., & D., L. (1989). Innovation and learning: the two faces of R&D. *The Economic Journal*, 99(397), 569-596.
- Cohen, W., & Levinthal, D. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35, 128-152.
- Dasgupta, P., & David, P. (1994). Toward a new economics of science. *Research Policy*, 23(5), 487-521.
- Della Malva, A., Kelchtermans, S., Leten, B., & Veugelers, R. (2013). Basic science as a predescription for technological breakthroughs in the pharmaceutical industry. *conditionally accepted at Journal of Technology Transfer*.
- Du, J., Leten, B., & Vanhaverbeke, W. (sd). Managing open innovation projects with science-based and market-based partners. *Research Policy*, forthcoming.

- Fabrizio, K. (2009). Absorptive capacity and the search for innovation. *Research Policy*, 38(2), 255-267.
- Fleming, L., & O., S. (2004). Science as a map in technological search. *Strategic Management Journal*, 25, 909-928.
- Forti, E., Franzoni, C., & Sobrero, M. (2013). Bridges or isolates? Investigating social networks of academic inventors. *Research Policy*, 42, 1378-1388.
- Fuller, A., & Rothaermel, F. (2012). Capturing technological opportunity via Japan's star scientists: evidence from Japanese firms' biotech patents and products. *Strat. Entrepreneurship Journal*, 6, 220-235.
- Fuller, A., & Rothaermel, F. (2012). When stars shine: The effect of faculty founders on new technology ventures. *Strategic Entrepreneurship Journal*, 6, 220-235.
- Furman, J., & MacGarvie, M. (2009). Academic collaboration and organizational innovation: the development of research capabilities in the US pharmaceutical industry. *Industrial and Corporate Change*, 18(5), 929-961.
- Gambardella, A. (1992). Competitive advantages from in-house scientific research: the U.S pharmaceutical industry in the 1980s. *Research Policy*, 21, 391-407.
- Gambardella, A., & Arora, A. (1990). Complementarity and external linkages: the strategies of the large firms in biotechnology. . *The Journal of Industrial Economics*, 361-379.
- Gambardella, A., Harhoff, D., & Verspagen, B. (2008). The value of European patents. *European Management Review*, 5(2), 69-84.
- Gittelman, M., & Kogut, B. (2003). Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. *Management Science*, 49(4), 366-382.
- Griliches, Z. (1986). Productivity, R&D and basic research at the firm level in the 1970s. *The American Economic Review*, 76(1), 141-154.
- Hagedoorn, J., & Wang, N. (2012). Is there complementarity or substitutability between internal and external R&D strategies? *Research Policy*, 41, 1072-1083.
- Hall, B., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *Rand Journal of Economics*, 36(1), 16-38.
- Hamilton, K. (2003). Subfield and level classification of journals. *CHI Report No. 2012-RCHI Research Inc.*
- Hess, A., & Rothaermel, F. (2011). When are assets complementary? Star scientists, strategic alliances and innovation in the pharmaceutical industry. *Strategic Management Journal*, 32(8), 895-909.
- Hess, A., & Rothaermel, F. (2012). Intellectual capital and the emergence of biotechnology: Trends and patterns: 1974-2006. *IEEE Transactions on Engineering Management*, 59(1), 65-76.

- Hicks, D., Isard, P., & Martin, B. (1996). A morphology of Japanese and European corporate research networks. *Research Policy*, 25, 359-378.
- Jaffe, A. (1989). The real effects of academic research. *American Economic Review*, 79(5), 957-970.
- Kaplan, S., Murray, F., & Henderson, R. (2003). Discontinuities and senior management: assessing the role of recognition in pharmaceutical firm response to biotechnology. *Industrial and Corporate Change*, 12(4), 203-233.
- Kelchtermans, S., & Veugelers, R. (2011). The great divide in scientific productivity; Why the average scientist does not exist. *Industrial and Corporate Change*, 20(1), 295-336.
- Kelchtermans, S., & Veugelers, R. (2013). Top research productivity and its persistence: gender as a double-edged sword. *Review of Economics and Statistics*, 95(1), 273-285.
- Kelchtermans, S., & Veugelers, R. (2013). Top research productivity and its persistence: Gender as a double-edged sword. *Review of Economics and Statistics*, 95(1), 273-285.
- Klevorick, A., Levin, R., Nelson, R., & Winter, S. (1995). On the sources and significance of inter-industry differences in technological opportunities. *Research Policy*, 24, 185-205.
- Laudel, G. (2002). What do we measure by co-authorship? *Research Evaluation*, 11(1), 3-15.
- Leten, B., Kelchtermans, S., & Belderbos, R. (2010). The impact of external and internal basic science on research productivity in the pharmaceutical industry. *Working paper, Department of Managerial Economics, Strategy and Innovation*, KU Leuven, N°MSI_1003.
- Leten, B., Kelchtermans, S., & Belderbos, R. (2011). Do firms benefit from investing in basic research? An empirical investigation for pharmaceutical firms. In F. De Beule, & I. Nauwelaerts, *Innovation and creativity: The driving force of Europe's economy?* Edward Elgar.
- Machado, J., & Silva, J. (2005). Quantiles for counts. *Journal of the American Statistical Association*, 100(472), 1226-1237.
- Mansfield, E. (1980). Basic research and productivity increase in manufacturing. *The American Economic Review*, 70(5), 863-873.
- Mansfield, E. (1995). Academic research underlying industrial innovations: sources, characteristics and findings. *The Review of Economics and Statistics*, 77, 55-65.
- Mansfield, E. (1998). Academic research and industrial innovation: An update of empirical findings. *Research Policy*, 26, 773-776.
- Melin, G., & Persson, O. (1996). Studying research collaboration using co-authorships. *Scientometrics*, 36(3), 363-377.
- Nelson R. (1959). The simple economics of basic scientific research. *The Journal of Political Economy*, 67(3), 297-306.
- Perkmann, M., & Walsh, K. (2007). University-industry relationships and open innovation: Towards a research agenda. *International Journal of Management Reviews*, 9(4), 259-280.

- Rosenberg, N. (1990). Why do firms do basic research (with their own monzy)? *Research Policy*, 19(2), 165-174.
- Rothaermel, F., & Hess, A. (2007). Building dynamic capabilities: Innovation driven by individual-, firm-, and network-level effects. *Organization Science*, 18(6), 898-921.
- Sauermann, H., & Roach, M. (2011). Not all scientists pay to be scientists: heterogeneous preferences for publishing in industrial research. *DRUID working paper*, No. 11-03.
- Sauermann, H., & Roach, M. (2012). Taste for science, taste for commercialization, and hybrid scientists. *DRUID conference*.
- Sauermann, H., & Stephan, P. (2013). Conflicting logics? A multidimensional view of industrial and academic science. *Organization Science*, 24(3), 889-909.
- Schartinger, D., Rammer, C., Fisher, M.M., & Frohlich, J. (2002). Knowledge interactions between universities and industry in Austria: sectoral patterns and determinants. *Research Policy*, 31(3), 303-328.
- Sorenson, O., J, R., & Fleming, L. (2006). Complexity, networks and knowledge flow. *Research Policy*, 35, 994-1017.
- Subramanian, A., Lim, K., & Soh, P. (2013). 'When birds of a feather don't flock together: Different scientists and the roles they play in biotech R&D alliances. *Research Policy*, 42(3), 1-18.
- Teece, D., Pisano, G., Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal* 18(7), 509-533.
- Thursby, J., & Tursby, M. (2011). Has the Bayh-Dole act compromised basic research? *Research Policy*, 40(8), 1077-1083.
- Toole, A. (2012). The impact of public basic research on industrial innovation: Evidence from the pharmaceutical industry. *Research Policy*, 41, 1-12.
- Trajtenberg, M. (Rand Journal of Economics). A penny for your quotes: Patent citation and the value of innovations. 1990, 21, 172-187.
- Westfall, J, Mold, J., & Fagnan, L. (2007). Practice-based-research-"Blue Highways" ON THE nih roadmap. *JAMA: The Journal of the American Medical Association*, 4, 403-406.
- Zucker, L., & Darby, M. (1996). Star scientists and institutional transformation: patterns of invention and innovation in the formation of the biotechnology industry. *Colloquium on Science, Technology, and the Economy*, 93, 12709-12716.
- Zucker, L., & Darby, M. (2001). Capturing technological opportunity via Japan's star scientist: Evidence from Japanese firms' biotech patents and products. *Journal of Technology Transfer*, 26, 37-58.
- Zucker, L., Darby, M., & Armstrong, J. (1998). Geographically localized knowledge spillovers or markets? *Economic Inquiry*, 36, 65-86.

Zucker L, Darby M., Armstrong J. (2002). Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. *Management Science*, 48(1), 138-153.

Figure 1: Sample firms with their innovative performance and percentage of co-publications

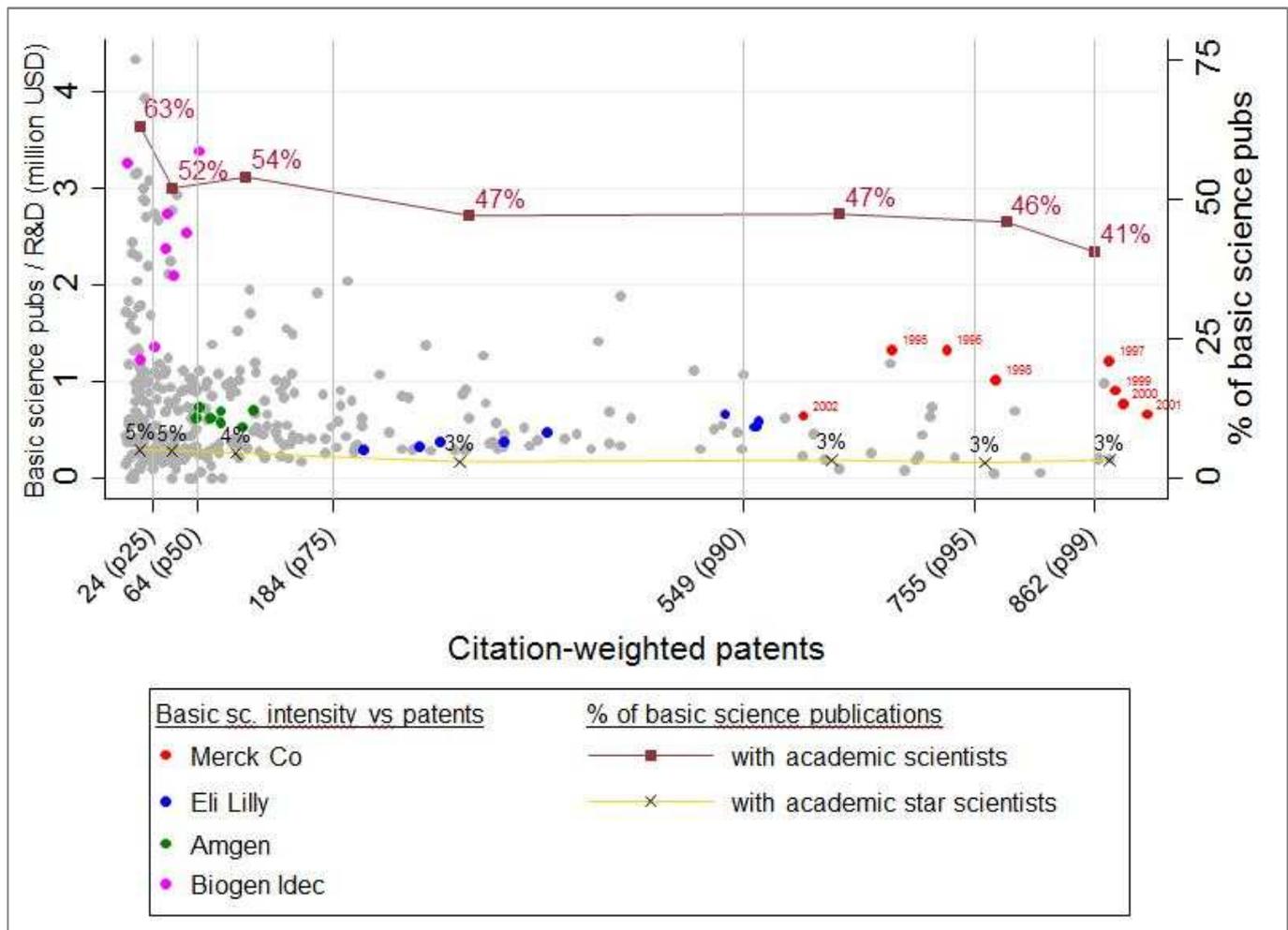


Table 1: variable means

Variable	Percentiles of citation-weighted patent output $i_{i,y}$				
	p0-p25 mean	p25-p50 mean	p50-p75 mean	p75-p90 Mean	p90-p100 mean
Citation-weighted patents _y	7.56	31.20	88.24	261.18	633.64
R&D (million USD)	64.97	162.18	325.14	1,177.36	2,225.93
Patents _(y-4, y-1)	22.42	48.34	117.66	362.55	859.79
Technological diversification (nr equivalent for patents _(y-4, y-1))	3.00	3.38	3.64	3.69	3.62
NPRs _(y-4,y-1) to external basic science publications/ patents _(y-4, y-1)	1.25	1.08	1.06	0.86	0.58
Basic science pubs _(y-4,y-1) / R&D _(y-4,y-1) (million USD)	1.37	1.52	0.70	0.58	0.47
% with university co-authors	0.57	0.59	0.50	0.49	0.47
% with university stars	0.04	0.03	0.05	0.03	0.03
% with translational star*	0.07	0.08	0.15	0.25	0.21
% in exclusivity	0.33	0.43	0.53	0.63	0.63
% with non-translational star	0.93	0.92	0.85	0.75	0.79
% in exclusivity	0.00	0.06	0.17	0.38	0.35
N _{firms} **	27	33	29	19	11

*Translational star indicates that the university star scientist also performs applied research with the firm

** For the average per percentile band, N_{firms} indicates the number of unique firms represented in the percentile band. As we have multiple observations of one firm across time (1995-2002), firms may occur in more than one percentile band.

Table 2: correlation matrix of the regression variables

	13.	12.	11.	10.	9.	8.	7.	6.	5.	4.	3.	2.	1.
1.Citation-weighted patents_y	-0.1407	-0.3460	-0.1311	0.3103	0.3721	0.1978	0.0387	-0.0219	-0.0873	0.1893	0.9175	0.6435	1.0000
2.R&D (million USD)	-0.2265	-0.5515	-0.2648	0.4538	0.4555	0.3085	0.0486	0.0022	-0.2451	0.2227	0.6632	1.0000	
3.Patents_(y-4, y-1)	-0.1328	-0.3778	-0.1674	0.3330	0.3600	0.2007	0.0256	-0.0245	-0.0923	0.1946	1.0000		
4.Technological diversification (nr equivalent for patents _(y-4, y-1))	-0.0046	0.1377	0.2423	0.1516	0.0797	0.0441	0.0606	0.1599	0.0289	1.0000			
5.NPRs_(y-4,y-1) to external basic science publications/ patents_(y-4, y-1)	-0.1067	0.1574	0.2604	0.0343	-0.0437	-0.0254	0.0247	0.1114	1.0000				
6.Basic science pubs_(y-4,y-1)/ R&D_(y-4,y-1)	-0.0767	0.1250	0.0878	0.0451	0.0064	0.0719	0.0415	1.0000					
7. % with university co-authors	-0.0031	0.0795	0.1663	0.1659	0.2707	0.3783	1.0000						
8. % with university stars	-0.1106	-0.1278	0.0083	0.0857	0.7005	1.0000							
9. % with translational star*	-0.1355	-0.1919	0.0148	0.2877	1.0000								
10. % in exclusion	-0.0919	-0.2209	0.0056	1.0000									
11. % of exclusive collaborations with non-translational star	-0.1128	0.5244	1.0000										
12.Biotech dummy	0.0968	1.0000											
13.Instrument dummy	1.0000												

Table 3: Quantile regression analysis: the effect of collaboration in basic science with university star scientist on technological performance

	Quantile parameter estimates					
	25%	50%	75%	90%	95%	99%
Log(R&D)	0.68*** (10.34)	0.55*** (3.25)	0.43*** (4.16)	0.31*** (25.38)	0.35*** (7.45)	0.33*** (17.98)
Patents/ R&D	1.45*** (9.23)	1.57** (2.20)	1.99*** (8.12)	2.11*** (17.27)	2.36*** (5.49)	2.82*** (16.92)
Technology diversification	0.13*** (4.47)	0.13 (0.72)	0.13 (1.28)	0.16*** (7.00)	0.15*** (8.92)	0.19*** (36.69)
Nr of non-patent references to external basic science	-0.22*** (-2.77)	-0.26 (-1.49)	-0.16 (-0.80)	0.04 (0.41)	0.41*** (11.16)	0.38*** (110.96)
Basic science publications / R&D:	0.13*** (4.31)	0.05 (1.10)	0.03 (1.32)	-0.01 (-1.23)	-0.00 (-0.28)	-0.01 (-1.58)
Of which %with academic co-authors	-0.12* (-1.75)	-0.25 (-0.78)	-0.18 (-0.52)	-0.14 (-1.56)	0.02 (0.08)	-0.09** (-6.43)
Of which %with academic stars	1.06 (0.77)	0.94 (0.13)	1.41* (1.68)	-0.22 (-0.48)	1.38 (1.61)	1.60*** (51.59)
Of which %translational stars	0.32 (1.19)	0.16 (0.43)	-0.11 (-0.35)	0.30*** (4.19)	0.65*** (12.18)	0.25*** (14.90)
Of which %exclusivity	-0.01 (-0.04)	0.05 (0.09)	0.09 (0.30)	0.07 (1.08)	-0.17 (-0.97)	0.22*** (16.68)
%exclusivity for non-translational stars	0.03 (0.23)	-0.01 (-0.03)	-0.17 (-1.18)	-0.11** (-2.51)	-0.18*** (-2.84)	-0.28*** (-13.68)
biotech company	0.57*** (4.45)	0.51 (0.95)	0.36 (1.62)	0.27*** (5.14)	0.04 (0.31)	0.13*** (6.22)
instrument company	-0.08 (-0.36)	-0.25 (-0.29)	-0.34 (-1.21)	-0.30 (-1.48)	-0.27* (-1.95)	-0.53*** (-27.35)
Constant	-5.24*** (-3.67)	-3.21* (-1.69)	-1.50 (-1.47)	-0.04 (-0.15)	-0.43 (-0.93)	-0.23 (-1.24)
Year dummies	<i>Includea</i>					
Nr of observations	456	456	456	456	456	456
Nr of firms	64	64	64	64	64	64
* p<0.10, ** p<0.05, *** p<0.01						